Image Fusion Experiment for Information Content

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Abstract – Recent developments in image fusion have produced a variety of approaches like image overlay, image sharpening, and image cueing through pixel, feature, or region/shape combinations. The applicability of these approaches and techniques differ on the image content, contextual information, and generalized metrics of image fusion gain. An image fusion gain can be assessed relative to information gain or entropy reduction. In this paper, we are interested in exploring the techniques and data available with the image fusion toolbox (from www.imagefusion.org) to assess the use of relative entropy analysis for metric evaluation, image fusion gain calculations, and assessment of fused images as templates for automatic target recognition. Examples are demonstrated for medical (PET/MRI), (CT/MRI) and environment (Visible/Infrared) examples. A mutual information measure of the image fusion quality can be an effective tool to characterize image terrain, content, and contextual information to cue higher-level fusion algorithms.

Keywords: Image Fusion, entropy, Mutual Information,

1 Introduction

Image Fusion is a growing topic for medical, military, and industrial applications and is defined as the process of combining information in two or more images of a scene to enhance viewing or understanding of the scene.[1] Image fusion, as opposed to strict data fusion, requires data representing every point on a surface or in space so be fused, rather than selected points of interest. [2] There are numerous medical examples presented of image fusion for registering and combining magnetic resonance (MR), positron emission tomography (PET), and computer tomography (CT) into composites to aid surgery. [3] Likewise, there are surveillance examples of image fusion for combining polarimetric synthetic aperture radar (SAR) and hyperspectral (HSI) data. [4] Another example is fusion of high-altitude images from Electro-optical/infrared (EO/IR), HSI, and SAR. [5] Finally, a third field is industrial applications that includes non-destructive (NDE) evaluation techniques to inspect parts. [6] In each of these examples, there are numerous opportunities for image fusion success in bringing together images from different sensors to help in decision-making and diagnostics.

Some benefits of image fusion include:

- Image overlay for displays
- Image sharpening for operator clarity
- Image enhancement through noise reduction
- Image mosaicking for enhanced spatial coverage
- Image registration for reference to world coordinates
- Enhanced clarity through feature amplification
- Segmentation through regional selections
- 3D estimation for scene calibration
- Image identification for tracking

Developments in the information fusion community have resulted in a consolidation of products and services for image fusion research at www.imagefusion.org. Many of the techniques and analysis are available for the community to explore different opportunities for image fusion research. It is the aim of this paper to show an Image Fusion experiment, using the data provided from the website. The experiment chosen for this paper explores the nature of relative entropy and mutual information as a measure of information content. [7].

Image fusion can have a goal to aid downstream fusion processes. Such details as image registration [8], target tracking [9], and automatic target recognition [10]. Many image fusion techniques have been explored such as wavelets [11], statistical approaches [12], principle components analysis, and various adaptive schemes [13]. An example of image fusion analysis includes mutual information (MI) metrics applied to SAR [10] and CT/MR brain images for registration [14]. Using the success for target recognition and registration, we utilized the MI approach to match scene information content (shown in Section 4).

For many applications, image fusion provides a pleasing perceptual display for a user to make better decisions which drives research in medical applications, [15], geo-spatial displays [16], and military situational awareness [17]. The exploration of image fusion techniques relies on an interplay between the user and the system to augment the feature and content of the image. [18] To enhance the user validation of the image fusion techniques, metrics are being designed to facilitate the image fusion quality. [19]
One of the issues surrounding image fusion is not only the various methods, but the determination of the quality of image fusion results. As part of the general theme of fusion evaluation for such things as user acceptance [20], target recognition [21], and mission effectiveness, there is a growing interest to develop methods that address the scored performance [22] of image fusion algorithms. Angell, [23] presented some image validation metrics of signal-to-noise (SNR) ratio, variance, and edge density; that were combined into cross-correlation, image quality, structural similarity, and peak SNR metrics. Angell applied these metrics over a host of standard image processing routines such as the Laplacian and wavelets. The initiation of evaluation techniques is important for downstream fusion processing. [24]

Given the diversity of applications and various methods of evaluation metrics, there is still open questions concerning when to perform image fusion and when separate images with separate processing is useful. While the answer will not be found in the paper, we are interested in exploring entropy as a measure of image fusion quality. Entropy can give a coarse metric as to the scene content, the complexity of the data, and some terrain pattern matching. The question to be explored is the usefulness of entropy used with fused images.

The rest of the paper is organized as follows. Section 2 describes the image fusion techniques and exploration topics. An entropy analysis using mutual information is described in Section 3. Section 4 describes the simulations and results. Section 5 provides a discussion and we conclude the paper in section 6.

2 Image Fusion Analysis

2.1 Image Fusion Process

Image Fusion has seen recent clarification in literature and publications. [22] From the taxonomy of data fusion techniques, there is an interest to describe image or object fusion on three levels: signal, feature, and decision level as shown in Figure 1.

If the image is of a 2D form, then the signal is a pixel. If the image includes 3D information such as terrain or tomography data, then the signal is a volumetric value. Given the signals, association of content can be explored (i.e. image fusion). However, for both feature and decision level fusion, the combined signal information is not done in signal space, but after the data has been exploited (e.g. image segmentation and feature extraction).

Image fusion requires a registration of 2D or 3D imagery for the purposes of spatially matching the signal, pixel, or volumetric image data for purposes of display to a user or for image processing routines. Pixel matching in particular can only be done with registered images, as detailed in Figure 2. Image processing includes feature and attribute detection, extraction, and segmentation. Higher level functions that utilize the features include object classification, recognition, and identification. Key to any of the image fusion techniques is processing the corresponding aligned pixels from each image for enhanced feature processing.

![Figure 2. Characteristics of Pixel Level Image Fusion.](image)

Adapted from Waltz, 2001.

Image fusion is a technique that should be explored with respect to the application. One example that suggests image fusion, is the reduction of data sent from an airborne platform. The combined image from such sensors as a Visible and IR system would reduce the data processing rate and increase data dissemination for such exploitations as tracking and targeting. Figure 3, describes a scenario in which we wish to explore metrics evaluation for fused image performance. The scenario is whether a terrain match can be gathered efficiently from a fused VIS/IR image versus the gain from each image separately.

![Figure 3. VIS/IR Image Fusion matching.](image)
2.2 Image Fusion Techniques

There are a variety of techniques that have been reported as valid image fusion processes. Some of the leading candidates are

1) Statistics based
2) Wavelet based
3) Scene content
4) Image overlay

To better understand these methods, we sought to do an experiment to understand the performance of these methods.

Some of the popular fusion techniques based on statistical analysis of the images are max or min and mean, and Principle Component Analysis (PCA). Assuming that images are collected simultaneously with accurate registration, images can be fused element wise, taking the maximum, the minimum, and the mean values.

PCA is an orthogonal linear transformation technique that transforms the multidimensional data sets to lower dimensions for image analysis without much loss of information content. The new coordinate system obtained by PCA transformation is such that the greatest variance by any projection of the data lies in the first coordinate (principle component), the second greater variance on the second coordinate, so on. Unlike other linear transforms which have a fixed set of basis vectors (Principle components), PCA basis vectors depends on the data set. This optimal transformation technique has more computational requirements as is the case of all statistical methods.

We use the popular wavelet based approach to find the decomposition coefficients for image fusion. The wavelet based method is available as the image fusion tool in the wavelet toolbox, which is used for fusing various registered images of the same size. The principle of image fusion using wavelets is to merge the wavelet decompositions of the two original images using fusion methods. All images that we tried fusing were registered images which allowed information combination at the pixel level.

Scene content and Image overlay are objective image fusion techniques whose functional characteristics depend on applicational requirement and image quality content.

Thus, using different fusion techniques like mean, max and min., Principle Component Analysis (PCA), and entropy; we obtained the fused images. We use the fused images for further analysis with the differential entropy pixel based approach described in Section 3.

2.3 Image Fusion Examples

The figures illustrated below show the registered and fused images using different fusion techniques like max or min, mean, Principle Component Analysis (PCA). In the first case, using the medical images supplied by Dr. Goshtasby, [26] we explored the techniques available for the brain image fusion processes. Shown in Figure 4 are the results of fusion a CT and MRI image. The color map used in displaying the images can highlight the regions of association for the corresponding images.

Figure 5 shows the case of the medical images and the VIS/IR image set available at www.imagefusion.org. [27] The fused images show different characteristics based on the sensor modality being fused. In each case, there is a corresponding information content in each of the fused images that is different than the original images.

![Fusion result using mean](image1)
![Fusion result using max. & min.](image2)

**Figure 4.** Fusion results using mean, max., min. for CT/MRI

In addition to the exploration of the images on the website, there was additional user community code supplied by various contributors such as Stavri Nikolov and Matt. [28]

![PCA Fusion result of MRI/PET](image3)
![PCA Fusion result of CT/MRI](image4)

**Figure 5.** PCA Fusion results for different image sets.

Based on the exploration of the image fusion algorithms and techniques, we sought to explore a image fusion metric based on content. The image content is based on mutual information, described in the next section.
3 Mutual Information

Mutual information as a subset of information theory is based on entropy calculations. Many entropy calculations are included in standard software techniques such as the basic Shannon entropy calculation. Most entropy calculations extend from the Renyi entropy, [29] which is a generalization of Shannon entropy. Renyi entropy is one of a family of functionals for qualifying the diversity, uncertainty or randomness of a system. The Renyi entropy is defined as the Shannon entropy. Renyi also defined a spectrum of generalized relative entropy, [29] which is a generalization of Shannon entropy. Renyi entropy is one of a family of functionals for qualifying the diversity, uncertainty or randomness of a system. The Renyi entropy is defined as:

\[ H_{\alpha} (X) = \frac{1}{1-\alpha} \log \left( \sum_{i=1}^{n} p_i^\alpha \right) \]  

(1)

where, \( p_i \) are the probabilities of \{x_1, x_2, ..., x_n\}. If the probabilities are all the same then all the Renyi entropies of the distribution are equal, with \( H (X) = \log n \). Otherwise the entropies are weakly decreasing as a function of \( \alpha \). In the limit that \( \alpha \) approaches 1, it can be shown that \( H \) converges to

\[ H_1 (X) = - \sum_{i=1}^{n} p_i \log p_i \]  

(2)

which is the Shannon entropy.

Renyi also defined a spectrum of generalized relative information gains (the negative of relative entropies), generalizing the Kullback-Leibler (KL) divergence:

\[ D_{KL} (P \| Q) = \sum_{i=1}^{n} p_i \log \frac{p_i}{q_i} \]  

(3)

which is the relative entropy [7], or discrimination gain which are all essentially the same.

Mutual information affords modeling techniques to arrive at image fusion, feature extraction, [30] and target recognition. Image content calculation that could be utilized for conducting approved image fusion, hypothesis detection, [31] and/or image segmentation. The entropy function provides the first and second differential values of the two images.

A measure of mutual information will determine the information-theoretic feature content. The identification of a target can be achieved by maximization of mutual information, which has been described by Viola and Wells [32]. Subsequently, we can use the relative entropy, or KL divergence parameter from Equation 3 to do terrain or target assessment. The goal is to obtain a learned estimate of the association, \( A \), that associates the target-measured orientation, \( T = f(k) \), and the detected target observation \( O \) by maximizing their mutual information over association estimate:

\[ \hat{A} = \max_A \{ I (T(k), O(A(x))) \} \]  

(4)

where \( x \) is a random variable that ranges over the cropped fused (e.g. EO/IR) image. For ease of notation, we will use \( T = T(k) \) and \( O = O(A(x)) \).

Mutual Information, defined using entropy, is

\[ I (T; O) = h(T) + h(O) - h(T, O) \]  

(5)

where \( h(\bullet) \) is the differential entropy of a continuous random variable, and is defined as:

\[ h(x) = - \int p_x(y) \log [ p_x(y) ] \, dy \]  

(6)

Given the random variable measurements in an image, information on a referenced \( x, y \) pixel can be used as a feature of orientation, or independently as length and width. The joint entropy of two random variables \( x \) and \( y \) is

\[ h(x, y) = - \int p_{(x,y)} (x, y) \log (p_{(x,y)} (x, y)) \, dx \, dy \]  

(7)

Mutual Information can also be expressed as:

\[ I (T; O) = h(O) - h(O \mid T) \]  

(8)

or

\[ I (T; O) = D \{ f(T, O) \| f(T) f(O) \} \]  

(9)

where \( h(y \mid x) \) is the conditional entropy which can be interpreted as a measure of uncertainty, variability, or complexity.

Information, in the association problem, is divided into three characteristic functions:

1) Entropy of the target, independent of \( A \),

2) Entropy of the image which the target is associated with, and

3) The negative joint entropy of the observation \( O \) with the Target \( T \).

A large negative value exists when the fused target image trained set and the observation fused image are functionally related. Basically, it learns associations where the observation \( O \) explains the target image \( T \) orientation above a desired threshold. Hence, (7) and (8) are learned associations for complexity reduction.

Viola used a stochastic gradient descent method to seek a local maxima of the mutual information criterion. The method employs histograms to approximate entropies and their derivatives. For this paper, we utilize the histograms as to approximate the entropies, as shown in Figure 6.
Let $I(t) = \{(i(s), y(s)), \ s = 0, \ldots, k\}$ be the total information available at stage $k$, consisting of $(i, y)$ measurement pairs, $i(s)$ being the sample feature and $y(s)$ the realized measurement at each epoch through stage $k$ for the feature $f$. Using this setup and derivation for differential entropy described with each pixel, we were interested in comparing the fused trained images measure with a test fused image set to determine if there was a match.

4 Simulations

We utilized the image fusion tool supplied by the imagefusion.org website to explore various outputs. Included in the analysis was the development of the relative entropy calculations that augmented the various techniques supplied by the tool.

4.1 Image Fusion Examples

From the image fusion tool, we sought to compare the relative entropy values in order to determine the quality of the image fusion result that would give a measure of image fusion quality.

Experiment 1: MRI/PET, CT/MRI Image Fusion

Here, we simulate the medical image process for a Magnetic resonance (MR), Positron Emission tomography (PET), Computer Tomography (CT) for a set of brain images, as shown in Figure 7.

As shown in Figure 7, the fused results present a rich set of feature information that could be used by a practitioner for diagnostics.

Experiment 2: Visible/IR Image Fusion

The following figures give the simulation result for a Visible/Infrared imagery. These are registered images (TNO-UN) obtained from www.imagefusion.org. The fused images presents us an interesting template for assessment with regards to Automatic Target Recognition (ATR). The case of fused image having the important information content (man standing - not seen in visible image) is the result that is going to provide surveillance detailed information for security purposes, as shown in Figure 8.

The fused results of these images give scope for interesting observations and analysis based on user’s objective and applicational requirement. Instance, CT density information and MRI soft tissue visualization would provide a comprehensive combination which can provide more hits during tumour detection.

The image fusion differential values are found for MRI and PET, fused and MRI, fused and PET; CT and MRI, fused and CT, fused and MRI; Visible and Infrared, fused and Visible, fused and Infrared Visible images.

4.2 Image Fusion Results

The following tables 1, 2, 3, show the entropy values for all the above combinations applied the images. From the analysis, we could then assess the normalized entropy difference as a measure of image matching.

<table>
<thead>
<tr>
<th>IMAGE 1</th>
<th>IMAGE 2</th>
<th>FIRST ENTROPY</th>
<th>SECOND ENTROPY</th>
</tr>
</thead>
<tbody>
<tr>
<td>MRI</td>
<td>PET</td>
<td>0.0988</td>
<td>0.5122</td>
</tr>
<tr>
<td>MRI</td>
<td>Fused (MRI/PET)</td>
<td>0.1501</td>
<td>0.7915</td>
</tr>
<tr>
<td>PET</td>
<td>Fused (MRI/PET)</td>
<td>0.5518</td>
<td>0.7918</td>
</tr>
</tbody>
</table>

Figure 6. Histogram of Probabilities.

Figure 7. Entropy Fusion results of Medical Images

Figure 8. Entropy Fusion results of Visible/ Infrared Images
### Table 2: Entropy values for CT and MRI

<table>
<thead>
<tr>
<th>IMAGE 1</th>
<th>IMAGE 2</th>
<th>FIRST ENTROPY</th>
<th>SECOND ENTROPY</th>
</tr>
</thead>
<tbody>
<tr>
<td>MedA (CT)</td>
<td>MedB (MRI)</td>
<td>0.1409</td>
<td>0.3182</td>
</tr>
<tr>
<td>MedA (CT)</td>
<td>Fused (CT/MRI)</td>
<td>0.1409</td>
<td>0.9020</td>
</tr>
<tr>
<td>MedB (MRI)</td>
<td>Fused (CT/MRI)</td>
<td>0.3182</td>
<td>0.9020</td>
</tr>
</tbody>
</table>

### Table 3: Entropy values for Visible & Infrared

<table>
<thead>
<tr>
<th>IMAGE 1</th>
<th>IMAGE 2</th>
<th>FIRST ENTROPY</th>
<th>SECOND ENTROPY</th>
</tr>
</thead>
<tbody>
<tr>
<td>Visible</td>
<td>Infrared</td>
<td>0.5444</td>
<td>0.5654</td>
</tr>
<tr>
<td>Visible</td>
<td>Fused (Visible/Infrared)</td>
<td>0.5444</td>
<td>0.9495</td>
</tr>
<tr>
<td>Infrared</td>
<td>Fused (Visible/Infrared)</td>
<td>0.4919</td>
<td>0.9495</td>
</tr>
</tbody>
</table>

For perfect matching of images, the relative entropy value should be zero. Thus, lower the entropy differences, the better matched the images are. This inference is verified from our experimental data. For instance, the fused MRI/PET image matches better with the MRI image as compared to the PET, which is verified by the lower entropy value for MRI and MRI/PET fused image. Additionally, Table 3 shows that the fused image entropy does worse for matching than the matching of the VIS to IR image.

Another interesting assessment is that the MI for the fused images was higher than each image separately. Figure 9 shows the results of the values for the medical images. From the analysis, we can see that the entropy increases from the fused images which is a result of the combination of pixel values that results from the increased diversity in information. The is seen from the aspect of the medical images, which is different than the test set used for the terrain analysis shown in Section 4.3.

4.3 Entropy metric for Image Fusion Analysis

The metric evaluation to fused images using the entropy approach is verified as an effective method in our analysis. Next, we tried to utilize the image fusion metric for terrain analysis as a measure of scene content. We utilized the images provided for various VIS/IR data for fusion results from the imagefusion.org website. An example of the images is shown in Figure 10.

![Figure 10. Representative images for terrain analysis.](image)

We then fused the VIS/IR images to get a fused-image database as hypothesized as a better representation of terrain for day/night conditions. Furthermore, we picked another test image set to determine the information content of the fused image for terrain comparison. Such an example of a test set of images is shown in Figure 11.

![Figure 11. Test image for terrain analysis.](image)

From Figure 11, it is easy for human inspection to determine the match with the trained set in Figure 10. If there were many images coming from an airborne platform, the user would lose attentional capability to focus on the screen. However, if there was an automated detection routine to cue the user as to the information content and hence (1) a possible location match or (2) target of interest (based on the entropy difference given accurate sensor positional accuracy), then the user would be able to focus attention when there was scene information needing further exploitation.

The key to this study is to explore a method of automatic terrain recognition based on the feature information content. In this case, a entropy-pixel measure for a cropped image could be part of a feature set. For instance, the upper right images in Figure 10 do not contain targets of interest, whereas the lower left images contain man-made objects that would warrant exploitation.
Two sets of Visible and Infrared images were taken from the Stavri’s Image set. For each set a fused image was obtained for five pairs respectively. The MI values for each set is tabulated as follows.

Table 4. MI for the first set of fused images

<table>
<thead>
<tr>
<th></th>
<th>Pair 1</th>
<th>Pair 2</th>
<th>Pair 3</th>
<th>Pair 4</th>
<th>Pair 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>MI</td>
<td>4.4783</td>
<td>4.4777</td>
<td>4.3414</td>
<td>4.6555</td>
<td>4.2579</td>
</tr>
</tbody>
</table>

Table 5. Entropy for the second set of fused images

<table>
<thead>
<tr>
<th></th>
<th>Pair 1</th>
<th>Pair 2</th>
<th>Pair 3</th>
<th>Pair 4</th>
<th>Pair 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>MI</td>
<td>5.5345</td>
<td>5.2295</td>
<td>5.2862</td>
<td>5.0719</td>
<td>4.9829</td>
</tr>
</tbody>
</table>

As can be seen from the table, the MI relative entropy values for a single set of images are closely matched. The images for each set were obtained for the same location, varying the noise conditions while capturing the image. A close match of MI values for different pairs indicates similar conditions under which the images were taken.

The experiment allows us to have a trained data set template. When we have MI value for an image in the particular area of interest (test image), we can come to a conclusion about the test image by looking at the template. The trained and test image should attain the same MI information content when the terrain information is closely matched.

Presented in Figures 12 and 13 are the plots for entropy values of each pair of images for varying noise and the respective fused image.

![Figure 12. Entropy Plot for Set 1](image)

![Figure 13. Entropy Plot for Set 2](image)

5 Discussion

Many times for data reduction, images will be fused which can alter the information content. For such applications as airborne platforms, image fusion and decision-level fusion are required before the image is transferred to the ground to save bandwidth and channel capacity. These bandwidth constraints require further exploration in metrics and image fusion techniques to optimize applications such as target recognition and feature-aided tracking. These issues might not be relevant for spatially-localized applications such as the medical imaging. However, applications such as telemedicine, might revisit the topic as related to image compression, storage, and matching.

The experiment demonstrated effective use of image fusion, the community supplied image fusion data sets and tools, as well as provided a exploration possibility over various applications. To this end, the details of the paper formed an effective experiment to understand image fusion and a possible metric for image content analysis.

The third issue is the metrics themselves. While the relative-entropy and MI [7] metric was useful for scene content experimentation and matching, further exploration is needed in the analysis to have a consistent representation of general trends. The MI metric has been successful for image registration [14], target recognition [10], and medical diagnostics. For novel contributions, we are further interested in clarifying its score performance and sensitivities as compared the other explored metrics.

The experiment presented in this paper should be characterized as demonstration of the usefulness of the imagefusion.org datasets as supporting challenge problems for the image fusion community.
6 Conclusion

In this paper, we present a mathematic description for image fusion mutual information analysis, and showed its usefulness in image fusion scene content matching. The future scope of this metric evaluation can extend itself to other applications like HSI/SAR fusion applications. The paper details an exploration study presented on the www.imagefusion.org website to include tools, data, and investigative study. Further work will include other data sets and analysis using the supplied information as well as work on mutual information to support change detection.

Acknowledgements: We would like to thank Dr. Goshatsby of Wright State University for his help, Dr. Nikolov for his guidance on resources available on the website, and significant useful comments from the reviewers.

References
[26] MRI & PET images from Kettering Medical Center.
[27] CT, MRI, Visible & Infrared TNO UN Camp images from www.imagefusion.org
[29] www.wikipedia.org